

# Path Clustering: Grouping in an Efficient Way Complex Data Distributions

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**Abstract:** This work proposes an algorithm that uses paths based on tile segmentation to build complex clusters. After allocating data items (points) to geometric shapes in tile format, the complexity of our algorithm is related to the number of tiles instead of the number of points. The main novelty is the way our algorithm goes through the grids, saving time and providing good results. It does not demand any configuration parameters from users, making easier to use than other strategies. Besides, the algorithm does not create overlapping clusters, which simplifies the interpretation of results.

**Keywords:** Cluster, grid, complexity, points, shapes.

## INTRODUCTION

In spite of the fact that many clustering algorithms have been proposed in the last years [1], it is still a challenge to find irregular shaped clusters from large data sets in acceptable time not demanding too many computational resources. Methods that are able to identify arbitrary shapes impose restrictions of processed data size sets in order to maintain admissible levels of memory usage and processing time.

In the context of Big Data and Data Mining, it is quite relevant the ability of finding clusters without knowing features of the data sets to be clustered. Often, these areas have to deal with large data sets that may produce clusters with arbitrary shapes from different sources, such as: geographic systems, medical systems, and sensors, among others.

This way, clustering algorithms should present some features, such as: ability of assembling clusters of arbitrary shapes and high dimensionality data, capacity of dealing with large data sets having noise and outliers, independence of data order and low time complexity. These characteristics of clustering techniques allow discovering patterns that were not forecast previously. Current clustering algorithms have facing problems to execute these tasks.

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Fernandes, R.Q.A. This work presents a new clustering algorithm, named Path Clustering, which  
Pinheiro, W.A. addresses these features, having better performance than some competitor  
Xexéo, G. B. algorithms existent in literature. Despite the existence of grid clustering  
De Souza, J. M. algorithms not be something new, the main novelty of Path Clustering is the  
way it goes through the grids, saving time and getting good results in terms of  
formed clusters. It considers points allocated in a space divided in small square  
forms, named tiles (subdivisions of a space in squares, cubes, etc). Neighbors  
tiles containing one or more points are grouped, which may create a clustering  
path. This strategy allows building clusters of irregular shapes, independently  
of data order, and with low complexity. In this context, a relevant cluster in this  
paper follows the definition related to Contiguous Cluster (Nearest neighbor  
or Transitive) given at [17]: “A cluster is a set of points such that a point in a  
cluster is closer (or more similar) to one or more other points in the cluster than  
to any point not in the cluster”.

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The experiments demonstrate our strategy is scalable and provide clusters of good quality when it is compared to other clustering algorithms. At the same time, it allows to find complex patterns from arbitrary data distributions, irregular or not.

The rest of our work is organized as follow: Section 2 presents the related work, Section 3 details the proposed algorithm, Section 4 shows the experiments and Section 5 presents our remarks and points out future works.

## RELATED WORK

The traditional clustering techniques generally divide clustering algorithms in two main classes: hierarchical and partitioning algorithms [2]. However, in the last years, many different techniques have been proposed trying to reduce the runtime, improve the quality and deal with multidimensional data [3]. These techniques have been applied in many different areas, such as Biomedical Informatics [19].

The hierarchical clustering algorithms make possible to have different visions of grouped objects and it includes agglomerative and divisive methods [4]. The agglomerative methods use a bottom-up strategy. They start with small clusters that are grouped in bigger clusters successively, having algorithms of complexity equal to  $O(n^2)$  in the best scenario. The divisive methods adopt a top-down strategy, dividing the clusters progressively. Thus, their complexity is  $O(2^n)$ , which is much worse than the complexity of agglomerative methods.

The partitioning clustering algorithms builds data partitions that are evaluated according to some criteria, as a distance between pairs of clusters. They include some strategies, such as: K-means and K-medoids Methods, and Density-Based Algorithms: Density-Based Connectivity Clustering and Density Functions Clustering [5].

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K-means aims at minimizing the average squared Euclidean distance of data from their centers. The centers can initially be chosen randomly and then they are recalculated until either a stop criterion is reached or a number of iterations are executed. K-medoids is similar to K-means, but an object that really exists represents the center of each cluster. The complexity of these algorithms is  $O(n)$ . But they tend to form Voronoi sets [6], failing to more complex distributions. Another problem of K-means is the necessity of a parameter that inform the number of clusters. Some authors [20] work for providing strategies to discover the number of cluster in a data set, which could reduce the necessity of getting this information from the user.

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Density-Based Algorithms [7], such as DBScan, define different clusters based on minimum number of points, radius of a region ( $r$ ), core points, reachable points and outliers. A core point is a point that can connect directly at least to a minimum number of points within distance  $r$  of it. Points that can be connected directly to a core point are called reachable points. All points that are not core points or reachable points are called outliers. Based on this, a cluster is formed by a core point together with all reachable points from it, core or non-core. These methods generally work with numerical attributes and do not produce good results if the clusters have densities too different. Their complexity is  $O(n \log n)$ .

Other strategies of data clustering aim at dividing the data space in segments limited by multi-rectangular shapes. These strategies include Grid algorithms [5]. It deals with geometric shapes to aggregate data sets. Therefore, it stops treating points individually, after allocating them in shapes. This approach produces algorithms with  $O(n)$  complexity, where  $n$  is the number of points. GRID algorithms may work with attributes of different types and multiple dimensions. Normally, Grid algorithms apply complementary strategies, such as: density, partitioning and hierarchical methodologies, providing better flexibility for different applications. Bang Clustering, STING, DOC, MineClus and INSCY are examples of Hybrid Grid Strategies. Many times these strategies use heuristics to prune points, clusters and/or dimensions, which may become difficult to measure with precision their complexity.

Bang Clustering [8], which is an improvement of GridClust [9], mixes some ideas of hierarchical clustering and density-based algorithms to build grids resolutions through dendograms, having complexity  $O(n)$  for several distributions and  $O(n^2)$  in the worst case [3].

STING [10] uses statistical information and some constraints, such as density of objects in a region, to generate hierarchy of cells. It builds a cell tree using a top-down strategy, where each cell can have one or more data points. The clustering process considers the density of cells similarly to Density-Based Algorithms. The tree can be build in  $O(n)$  time. If the tree has  $k$  leaves, the complexity for clustering

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Fernandes, R.Q.A. is  $O(k)$  in the worst case, since empty cells do not need to be stored in the tree [3].  
 Pinheiro, W.A. DOC [11] establishes a subspace cluster using hypercubes of fixed side-  
 Xexéo, G. B. length containing a minimum of points. A parameter sets the balance between  
 De Souza, J. M. the dimensionality and the number of elements to be clusterized. It uses a random  
 search algorithm to find the subspace from an initial seed of sampled points.  
 MineCLUS [12] is derived from DOC, however, it uses a deterministic strategy to  
 search the projected cluster based on a sample seed point.

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INSCY [13] uses a tree (SCY-tree) to produce high dimensional clusters. It compares each point of the base clusters in order to merge the base clusters having points in common, generating higher dimensional clusters. INSCY has complexity  $O(2^k n^2)$ , where  $k$  is the dimensionality of the maximal subspace and  $n$  corresponds to the size of a data set.

Table 1 shows a comparison of some attributes of the clustering methodologies presented previously. One of the problems involves to set the best values of the algorithms parameters, because some of them are not intuitive for regular users and demand some time and experimentation to reach correct values (for each clustering scenario).

Our approach, which is better detailed in the next Section, uses the number of points to build grid resolutions automatically. Therefore, our algorithm does not demand any parameter from users. The concept of neighbor's tiles forms clusters, which makes the algorithm simple, less complex and faster than other initiatives, keeping a good level of quality for the clusters. The clusters are assembled when the algorithm walks through the tiles. Tiles containing one or more points that have as neighbor another tile containing also one or more points receive the same color. When there is no path (i.e. one or more tiles containing one or more points) that connects tiles containing one or more points, these tiles receive different colors. Thus, as colors are related to clusters, they belong to different clusters.

Table 1: Algorithms Comparison

Algorithms	Parameters	Ability of building clusters with arbitrary shapes	Data order	Complexity of Algorithms ( $n$ = number of points; $k$ = number of grids)
<b>Hierarchical Clustering</b>	Points and Minimal Distance among groups	Reasonable.	Some implementations are dependent of data order (average linkage) and others are not suitable to deal with noise (Single or complete linkage) (Khan, L. & Luo, F., 2005).	Divisive is $O(n^2)$ and Agglomerative is $O(2^n)$ .

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Algorithms	Parameters	Ability of building clusters with arbitrary shapes	Data order	Complexity of Algorithms ( $n$ = number of points; $k$ = number of grids)
<b>K-means and K-medoids</b>	Points and Number of clusters.	Limited. They tend to form Voronoi sets and they fail for distributions that are more complex.	They depend of data order. They are sensitive to initialization.	$O(n)$ .
<b>Density-Based Algorithms</b>	Points, Radius $r$ and Minimum Number of Points.	Reasonable. They do not produce good results if the clusters have densities too different.	They do not depend of data order.	DBScan ( $n \log n$ using an accelerating index structure and for non-degenerated data and $O(n^2)$ in the worst case).
<b>GRID Hybrid Algorithms</b>	Vary according to the implementation.	Very good. The challenge is to find the correct resolution (grid size) for different distributions.	Generally, they do not depend of data order.	Bang Clustering is $O(n^2)$ and STING is $O(n)$ for building the tree and $O(k)$ for clustering. DOC and MineClus use heuristic (authors do not discuss algorithm complexity). INSCY is $O(2^k n^2)$ .
<b>Path Clustering</b>	Points.	Reasonable.	It does not depend of data order.	$O(t)$ , where $t$ is the number of tiles.

In this work, the following algorithms are compared to Path Clustering: K-means, DBScan, INSCY, DOC and MineClus. Some of these algorithms can optionally generate overlapping or non-overlapping clusters. In this work, we set all algorithms in order to not produce overlapping clusters.

## PROPOSED APPROACH

To illustrate our strategy, we generate a data set represented by points in a space. Fig. 1 shows these points (graph A) and also presents some results (graphs B, C and D) obtained using some basic ideas of Path Clustering algorithm for three different resolutions (different number of tiles).

The first resolution divides the space in one hundred (ten x ten) tiles. If a tile contains one or more points, it receives a color. A tile containing one or more points that has a contact with other tile also containing one or more points receive the same color. Tiles containing one or more points separated by tiles containing no points receive different colors. This strategy builds the clusters showed in Fig. 1 (graph B).

The second resolution divides the space in ten thousand (100 x 100) tiles. It applies the same strategy used previously, building the clusters showed in Fig. 1 (graph C).

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Fernandes, R.Q.A. Comparing the results obtained by these resolutions, it is possible to observe that  
Pinheiro, W.A. the latter provides clusters that are closer to the expected from the original data  
Xexéo, G. B. distribution.  
De Souza, J. M. However, if we continue dividing the space in more tiles (1000 x 1000 tiles), as  
presented in Fig. 1 (graph D), they become too small. In this case, some tiles do not touch  
each other as they should (tiles distance is smaller than points distance), which produce  
more clusters than expected. Thus, the analysis of the proposed strategy demonstrates  
the relevance of choosing the correct number of tiles to obtain good results.

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For the sake of simplification, in this paper, we consider that all points are contained in a space of two dimension (axis  $x$  and  $y$ ) with a square format.

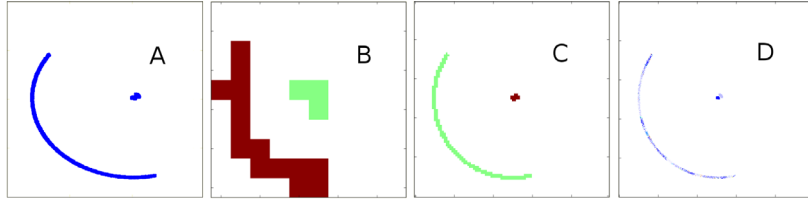


Figure 1: Path Clustering Algorithm for three different resolutions

To reach good results, it was defined that the maximum resolution, that can vary according to the number of points, should generate a complexity lower or equal to  $O(n)$ . Besides, if necessary, the transition among resolutions should be done easily. For example, four tiles in a flat space could be transformed in one big tile for the next resolution. In this case, the tiles of previous resolutions are equivalent to points for the next (lower) resolution. Thus, resolution was defined as a power of two, in order to make easier generating clusters for other resolutions through reuse of previous results (merging smaller tiles). Therefore, the results of higher resolutions can be used to generate results for lower resolutions.

In this context, this work defines Resolution Scale ( $RS$ ) as:

$$RS = 2^x \quad (1)$$

Where:

$$x = \text{upper limit of } [\log_2((\text{number of points})^{(1/\text{number of dimensions})})] \quad (2)$$

For instance, if the number of points is 100 and the number of dimensions is 2, then  $RS$  is equal to 16. If the space size that contains the points is equal to 20cm x 20cm, then the tile-side size is  $20/16=1.25$  and the total number of tiles is  $16 \times 16$  (total of 256 tiles).

In this case, the next inferior resolution would merge each four tiles in one, generation  $8 \times 8$  tiles (total of 64 tiles). In this paper, the proposed algorithm uses the higher resolution value to build the cluster. This algorithm has the following properties:

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1. It finds the maximum number of tiles considering only the number of points;
  2. It paints tiles without considering density of points;
  3. It uses a greedy strategy, just looking for local neighbors. Thus, it depends on the tiles size;
  4. It has the complexity that is given by the maximum number of tiles (maximum  $RS$ ) that is  $O(n)$ .
  5. It is independent of data order; and
  6. It has the capacity of finding clusters with arbitrary shapes in an efficient way.
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Considering this, the pseudocode of the algorithm is presented as follows ( $\leftarrow$  means ‘to receive’ and  $==$  means ‘is equal to’):

**Algorithm PathClustering**

*Input:  $P$  points*

*Output:  $T[\text{resolution}]$  list of colored tiles*

1.  $\text{num-of-points} \leftarrow \text{points from } P$
  2.  $S \leftarrow \text{calculate the minimum space in a square format necessary to contain all points from } P$
  3.  $\text{number of dimensions} \leftarrow 2$  (for a flat space)
  4.  $X \leftarrow \text{superior limit of } [\log_2((\text{num-of-points})^{(1/(\text{number of dimensions}))})]$
  5.  $RS \leftarrow 2^x$
  6.  $N \leftarrow (RS)^2$  (approximately equal to num of points )
  7.  $\text{Tiles}[] \leftarrow \text{Create } N \text{ tiles in } S, \text{ dividing } S \text{ in } RS \times RS = N \text{ tiles}$
  8.  $\text{Groups}[] \leftarrow \text{Create } N \text{ groups in } S \text{ (Each group can contain one color and one or more tiles)}$
  9.  $\text{Colors}[] \leftarrow \text{Create } N \text{ colors}$
  10. **While**  $t = \text{Tiles.next}$  (from left to right, top to bottom):
    - 10.1. **if**  $t$  contains some point  $p$  from  $P$  in  $S$  then  $t.\text{point} = \text{true}$  else  $t.\text{point} = \text{false}$
  11. **While**  $t = \text{Tiles.next}$ :
    - 11.1.  $\text{group} \leftarrow \text{Groups.next}$
    - 11.2.  $\text{color} \leftarrow \text{Colors.next}$
    - 11.3. **if**  $t.\text{point} == \text{false}$  then continue
    - 11.4. **if**  $t.\text{point} == \text{true}$  and  $t.\text{group}$  is null then
      - 11.4.1.  $\{t.\text{group} \leftarrow \text{group}; \text{group.color} \leftarrow \text{color}; \text{group.tiles} \leftarrow t\}$
    - 11.5. **if**  $t.\text{group}$  is not null then
      - 11.5.1.  $\{\text{group} \leftarrow t.\text{group}\}$
    - 11.6.  $\text{NE} \leftarrow \text{find neighbors of } t \text{ in Tiles (Up to 8 neighbors)}$
    - 11.7. **While**  $\text{ne} = \text{NE.next}$ : (Check neighbors' groups)
      - 11.7.1. **if**  $\text{ne.group}$  is not null and  $\text{ne.group} \neq t.\text{group}$  then
        - 11.7.1.1.  $\{\text{add ne.group to t.group (generates a bigger t.group where the color is kept)}\}$
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## EXPERIMENTS

To compare the results obtained and execution time of Path Clustering with other algorithms of equivalent complexity, we carried out a set of experiments. We selected the following algorithms: K-means, DBScan, INSCY, DOC and MineClus (one or more representative of each category showed in Table 1, except by hierarchical clustering). The hardware used in the experiments was an Intel Core i3 3.6GHz processor with 4GB RAM and the software used was Ubuntu 14.04.4 LTS. We used implementations of the algorithms kindly shared on web. The implementation of K-means and DBScan were obtained in python [15]. For INSCY, DOC Clustering and MineClus we used the executable software in java from [16].

To compare the algorithms, we built two classes of distributions: Gaussian distributions and Radial distributions. These distributions took as base five random points in a flat space. Therefore, the maximum of five relevant clusters could be obtained. Doing this, we tried to compare the algorithms in different scenarios using just two dimensions. A future work will compare our strategy in a scenario of high-dimensional data. The distributions considered distributions of 100 up to 10000 points. A number of points higher than 10000 was not run because some algorithms caused a high memory consumption avoiding completing these experiments in an acceptable time.

For repeatability, the algorithms configurations used in the experiments are presented in Table 2. For Grid-based algorithms, when possible, we set similar conditions when it was possible.

Table 2: Algorithms Parameters

Algorithm	Parameters
K-means	number of clusters = 5
DBScan	eps=0.1, min_samples=10
INSCY	Density=1.0, epsilon=1.0, gridSize= number of points, maximalClusterRate=0.0, min-Points=1.0, minSize=1, usingKernel=1
DOC	alpha*number of points = 1, beta=0.1 , maxiter=1024, k=5, w=1.0
MineClus	alpha*number of points = 1, beta=0.1 , maxiter=1024, k=5, w=1.0, numBins = 1

Fig. 2 shows a matrix of graphs containing Gaussian distributions. Each row corresponds to the distributions of 100, 500, 1000, 5000 and 10000 points, respectively. The columns corresponds to the results produced by the algorithms: K-means, DBScan, INSCY, DOC, MineClus and Path Clustering. Different clusters are represented by different colors in the graphs. For DBScan, black color represents points not grouped. DOC and INSCY may prune some points.

Fig. 3 shows a matrix of graphs containing Radial distributions. The graphs obey the same pattern used in Fig. 2.

[18] considers that human vision is efficient to find cluster in two dimensions. Therefore, in this paper, relevant clusters are identified visually. In the case of Gaussian distributions, it was obtained the following number of clusters: four clusters for the distribution of 100 points, four clusters for the distribution of 500 points, five clusters for the distribution of 1000 points, five clusters for the distribution of 5000 points and four cluster for the distribution of 10000 points. In the case of Radial distributions, it was obtained the following number of clusters: four clusters for the distribution of 100 points, five clusters for the distribution of 500 points, five clusters for the distribution of 1000 points, five clusters for the distribution of 5000 points and four cluster for the distribution of 10000 points. These values can be verified observing the graphics of Fig. 2 and Fig. 3.

Visually, it possible to observe for Gaussian and Radial distributions that Path Clustering had better results in terms of time than the other algorithms. Besides, in terms of cluster discovery, Path Clustering also had good results for all distributions.

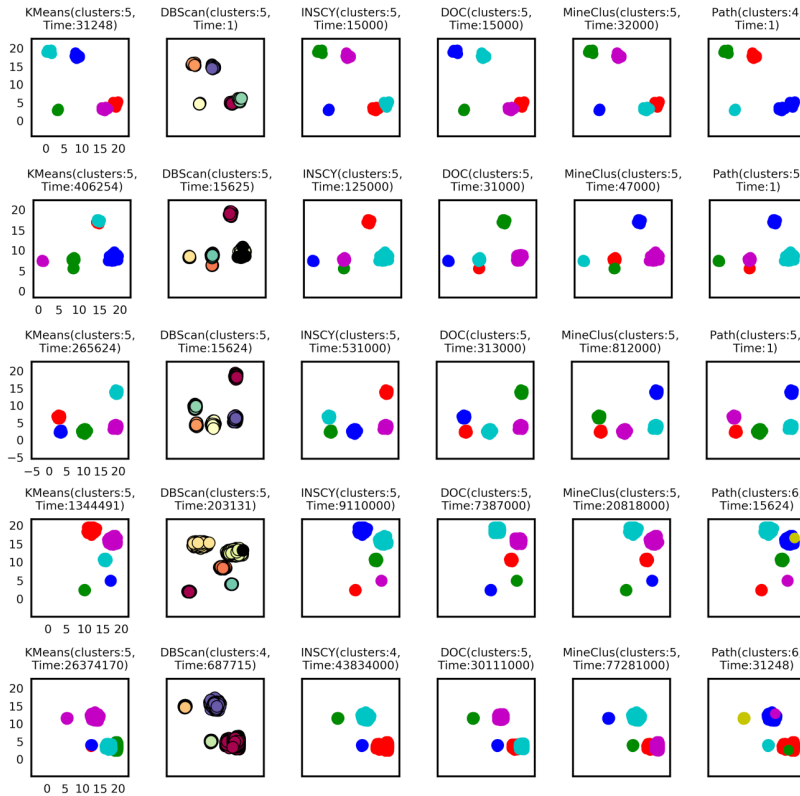


Figure 2: Gaussian distributions and clusters

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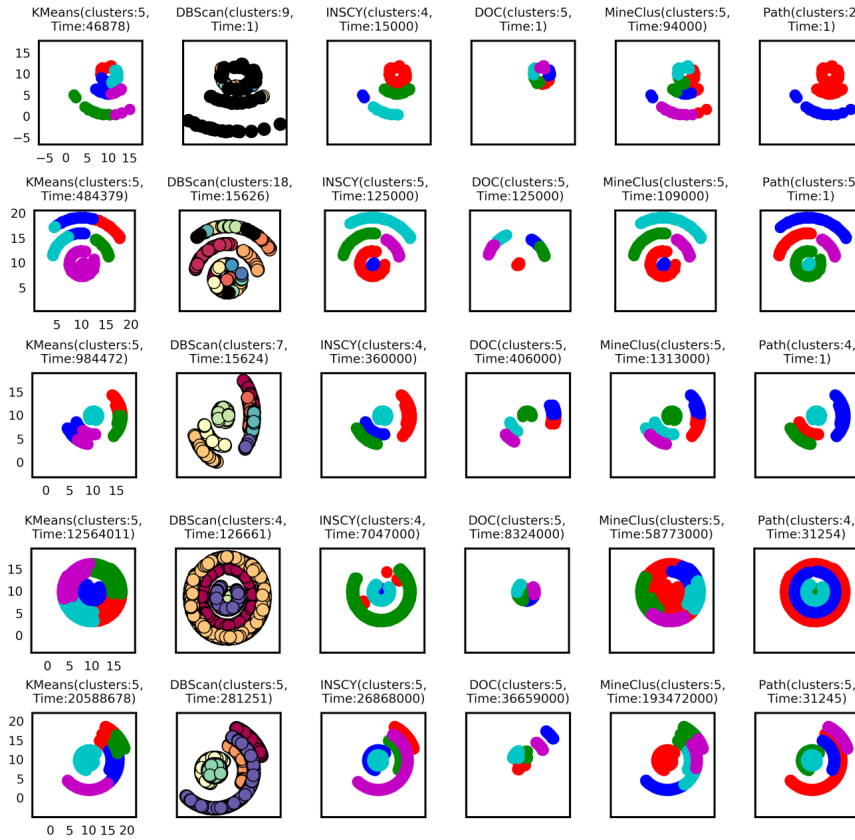


Figure 3: Radial distributions and clusters

Table 3 and Table 4 reveal the execution time (in microseconds) of the six algorithms for Gaussian and Radial distributions, considering 100, 500, 1000, 5000 and 10000 points. An average runtime is resulted of five executions of an algorithm.

Table 3: Average Runtime for Gaussian Distributions

Number of Points	Kmeans	DBScan	INSCY	DOC	MineClus	PathClustering
100	31248	<1	15000	15000	32000	<1
500	406254	15625	125000	31000	47000	<1
1000	265624	15624	531000	313000	812000	<1
5000	1344491	203131	9110000	7387000	20818000	15624
10000	26374170	687715	43834000	30111000	77281000	31248

Table 4: Average Runtime for Radial Distributions

Number of Points	Kmeans	DBScan	INSCY	DOC	MineClus	PathClustering
100	46878	<1	15000	<1	94000	<1
500	484379	15626	125000	125000	109000	<1
1000	984472	15624	360000	406000	1313000	<1
5000	12564011	126661	7047000	8324000	58773000	31254
10000	20588678	281251	26868000	36659000	193472000	31245

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Fig. 4 shows the total average time comparison (in microseconds) for Gaussian and Radial distributions, considering the values of Table 3 and Table 4. Axis Y is in logarithm scale. The results showed that, considering these two distributions, Path Clustering was more than 10 times faster on average than the second faster algorithm: DBScan.

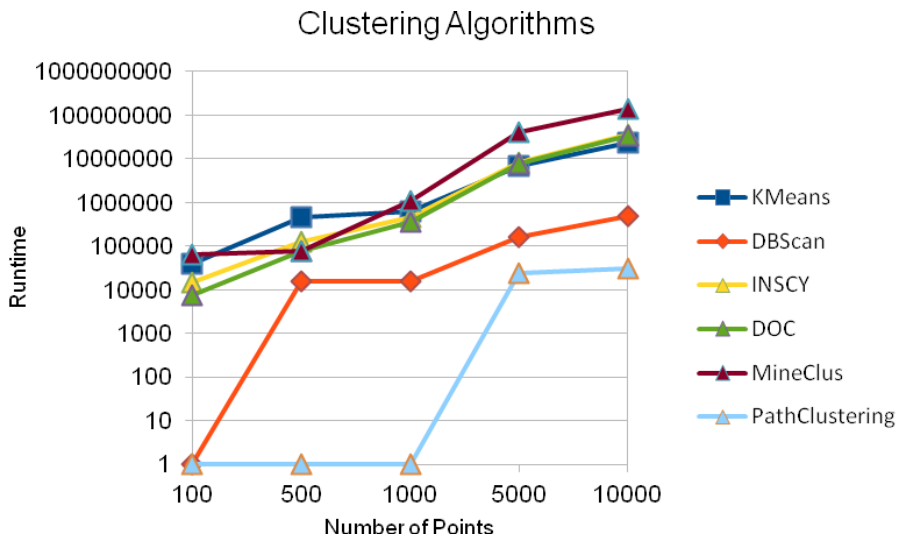


Figure 4: Total Average Runtime

Additionally, to measure the quality of the results, we used two metrics: precision and recall, derived from the Information Retrieval area.

Precision can be defined as the number of relevant returned results divided by the number of returned results [14]. We adapted this concept for cluster scenario, using precision as the as the number of relevant returned clusters divided by the number of returned clusters.

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Recall can be defined as the number of relevant returned results divided by the number of relevant results [14]. We used this as the number of relevant returned clusters divided by the number of relevant clusters. In our experiments, the maximum number of relevant clusters was five.

Fig. 5 presents the precision results for Gaussian distributions. Fig. 6 shows the recall results for Gaussian distributions. In three of five tests, Path Clustering got the best results for precision and recall.

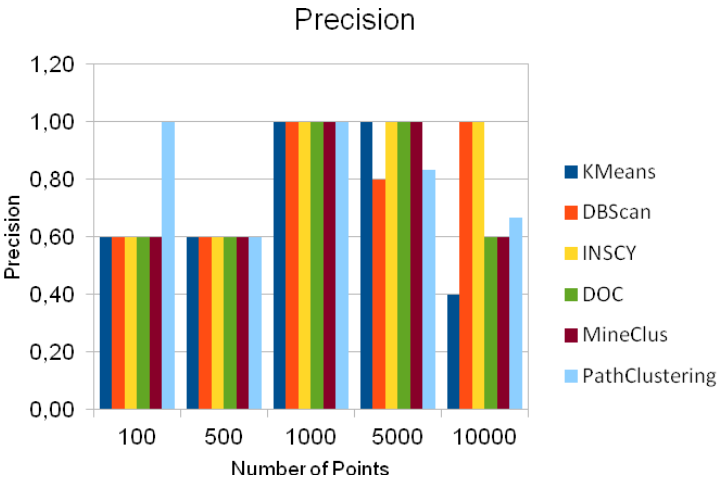


Figure 5: Precision for Gaussian Distributions

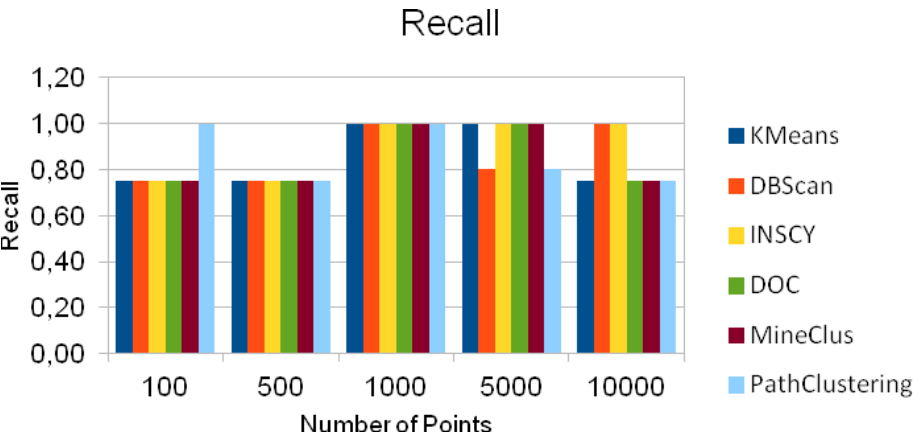


Figure 6: Recall for Gaussian Distributions

Fig. 7 presents the precision results for Radial distributions. It is possible to notice that Path Clustering got the best possible results in all cases.

Fig. 8 shows the recall results for Radial distributions. In four distributions, Path Clustering got the higher recall values.

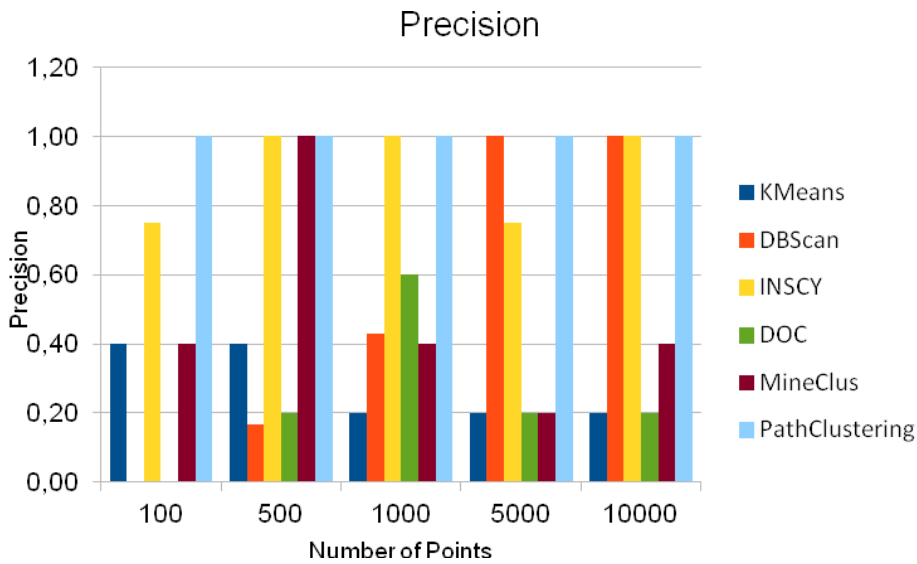


Figure 7: Precision for Radial Distributions

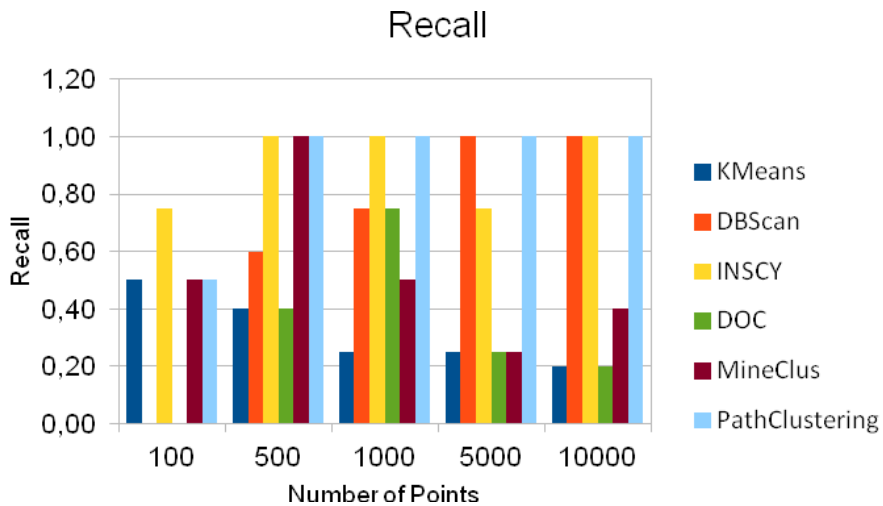


Figure 8: Recall for Radial Distributions

It important to mention that Path Clustering used an automatic configuration that does not demand any parameter from users. It makes the algorithm easier to use but it may reduce its precision and recall in some cases. One strategy to improve the results is to adjust the number of grids manually in case of necessity, increasing or reducing slightly this number. In future works, we intend

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Fernandes, R.Q.A. to develop a strategy to calculate the best number of grids according to the  
Pinheiro, W.A. distribution and number of points.

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De Souza, J. M.

## CONCLUSION

This paper presents a grouping algorithm named Path Clustering. It is a clustering grid algorithm that divides data space in segments limited by square shapes called tiles. The way used to navigate from one tile to another provides a new faster strategy to group data. It uses a greedy strategy, navigating through local neighbors following a specific path. Tiles containing one or more points separated by tiles containing no points receive different colors. Different colors indicate different groups.

After allocating data items (points) in geometric shapes in tile format, the complexity of our algorithm is related to the number of tiles instead of the number of points. Thus, the number of tiles is fundamental to reduce the complexity of our algorithm. In our strategy, a tile is represented by a square shape and the square-side size is a number related to a concept named Resolution Scale. In order to keep a balance between low complexity and good results for different data distributions, we proposed that maximum Resolution Scale should provide a complexity of  $O(n)$ , reducing space in memory and time of processing when compared to other algorithms.

Other interesting characteristic is that the algorithm presented in this paper does not require parameters from users beyond the data set itself, making easier to use than many other algorithms.

It was performed a comparative experiment considering Path Clustering and other five algorithms. The experiments demonstrated our strategy is scalable using two type of distributions (Gaussian and Radial) with different number of points. Path clustering showed the best performance in terms of time. Besides, their clusters get a good precision and recall in most part of tested distributions, considering the idea of a Contiguous Cluster (Nearest neighbor or Transitive). At the same time, it allows to find complex patterns from arbitrary data distributions, irregular or not.

Path Clustering implementation used in this work did not apply concurrent computing to execute the processes. Concurrent algorithms can execute processes in parallel, reducing processing time. Thus, we intend to implement this feature in future works, allowing to reduce even more the execution time for grouping data. Besides, we intend to compare the algorithm in a high-dimensional data scenario and calculate automatically the best number of grids according to the distribution and number of points.

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